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A Survey on Advanced Segmentation Techniques for Brain MRI Image Segmentation

Rupika Nilakant[#], Hema P Menon[#], Vikram K[#]

[#]Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore
Amrita Vishwa Vidyapeetham, Amrita University, India
E-mail:cb.en.u4cse14040@cbstudents.amrita.edu; p_hema@cb.amrita.edu; cb.en.p2cvi15015@cb.amrita.edu

***Abstract*— This paper presents a survey of advanced methods for segmenting the MRI (Magnetic Resonance Imaging) image of the brain. Segmentation of the brain is a challenging task because it requires more emphasized methods to differentiate each of the regions present in the brain image. The intensity differences between the different regions in the brain MRI image are very less, making it difficult to automate the entire segmentation process. Hence, a thorough understanding of the existing segmentation algorithm is essential for accurate segmentation. The segmentation algorithms surveyed in this work are Neural Network Model, Self-Organizing Maps, Radial Basis Function, Back Propagation, Fuzzy C-Means, Deformable Models, Level Set Models, Genetic Algorithm, Differential Evolutionary Algorithm, Hybrid Clustering and Artificial Intelligence. Such a survey would be helpful for researchers working in the field of brain image segmentation. The paper discusses the complexities in the segmentation algorithm and also the challenges in segmenting the brain MRI images. The segmentation outputs and analysis of the existing literature has also been discussed. The major criteria and their advantages in the segmentation of each algorithm have been reported accordingly in the observations.**

***Keywords*— Magnetic Resonance Imaging (MRI); brain image; segmentation; neural networks; deformable models; fuzzy c-means**

I. Introduction

Medical Imaging is the process of producing a visual impression of the internal portions of a human being for further analysis of clinical roles and medical purposes. Also, it can be viewed for gaining knowledge of the functions of the organs and tissues in a human body. Brain images can be acquired by various methods like i) Magnetic Resonance Image (MRI), ii) X-radiation (X-ray), iii) Polyethylene terephthalate (PET), iv) Computed Tomography (CT), v) Functional MRI (fMRI), vi) Single-photon Emission Computed Tomography (SPECT). In this survey paper, the technique of MRI has been addressed. The Axial View MRI will be a series of images from below the chin to the top of the head, Coronal View will be from the back of the head to the nose and the Sagittal View MRI was taken from one side of the ear to another ear.

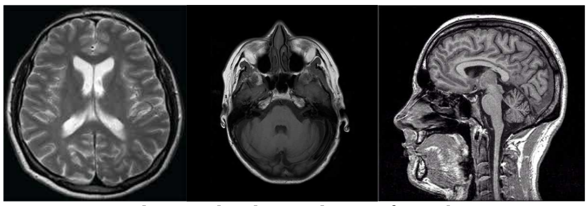


Fig. 1 Axial, coronal and sagittal view of MRI brain image

The brain of a human contains different types of regions in it. The three types of the major areas that are present in the brain images are namely: i) White Matter (WM), ii) Grey Matter (GM) and iii) Cerebro-spinal Fluid (CSF) is as shown in Fig. 1. The main objective in most of the segmentation process of medical imaging will be on extracting these regions and highlighting them accordingly.

Image Segmentation is the technique of partitioning an image into several regions based on the set of pixels and intensities in the digital image. Each of the regions that have been differentiated from one to another is based on its characteristics (i.e. color, texture or intensity). The White Matter, Grey Matter and CSF have been extracted using Image Segmentation techniques [1]-[4] and also the tumor detection in MRI Brain Image can be segmented by various studies [5]-[9]. M.El-Melegy et.al [2] proposed a nonparametric technique in such a way that it segments the 4 types of tissues on the MRI brain images, namely WM tissue, GM tissue, CSF and the remaining tissue as Non-Brain tissue. This paper concludes that it gives better performance in segmentation even at a higher degree of noise and bias. Shanthi et.al [10] has proposed a system of segmenting the DICOM images of the brain using seed growth and the thresholding technique. This paper shows that the highfrequency speckles in the images have been removed and gives good results. Unsupervised segmentation methods based on random walks proposed by C. Desrosiers [11] has been involved in segmenting the MRI of a brain image. The computed results on 3D Brain MRI from the IBSP (i.e., Internet Brain Segmentation Repository) shows that the computation is really efficient and performs well. Siddique et.al [3] used a method of region growing technique and seed pixel for the automatic segmentation of a brain MRI image. This paper implements in the exact categorization of the brain parts such as WM, GM and CSF and the ventricular regions.

Section II gives the literature survey and Section III gives our summary and observations that we went through the survey papers and Section IV gives the conclusion of the survey.

II. Material and Method

In this survey, we present the various types of segmentation methods for partitioning the MRI images. Basically, they are of two types: i) Basic Segmentation Methods and ii) Advanced Segmentation Methods. The advanced segmentation methods are more accurate than the basic segmentation methods. The methods may be divided into many types such as i) Manual Segmentation, ii) Hybrid Segmentation Methods, iii) Thresholding, iv) Atlas-Based Methods, v) Intensity-Based Segmentation, vi) Surface-Based Methods, vii) Region Growing, viii) Classification, ix) Clustering, x) Neural Network Methods.

The survey of the MRI brain image can be for segmenting the tissues of the brain or identifying the tumor detection in the process [12]-[14]. A common comparison of the different MRI segmentation methods given by Jun Yang and Sung-Cheng Huang [14] has been proposed in segmenting the brain image. This evaluates the manual segmentation methods and the proposed method provides faster and more measures of the objective in comparing all the MRI segmentation methods.

TaoSong et.al [12] proposed a method of segmentation in MRI brain image into WM, GM, CSF using hierarchical tissue segmentation method. Verma et.al [13] proposed three different algorithms such as k-means, Fuzzy C-Means (FCM) and Improved Mountain Clustering technique for the segmentation of brain image. This paper concludes that the performance is found to be the best on Improved Mountain Clustering technique. Arunkumar et.al [15] had proposed a system of the optimization algorithm to detect the ventricle region or the eyeball region of the MRI Brain Image. Menon et.al [16] has proposed a system of generating atlas-based on the 3 views and also segmented the regions of the caudate, ventricle, putamen and thalamus present in the brain from the right and left cerebral of the axial view in the MRI image.

A. *Process of Segmentation*

The MRI of a brain image is partitioned into several regions based on its intensity. The main aim of segmentation is to differentiate the different regions in an image and then label each region into its respective characteristics. The objects/boundaries in the images, like lines, curves etc., are located using segmentation algorithms. Each region that contains different portions varies from the other but shares certain characteristics. A collective set of areas that are extracted from the full picture or from a lot of contour regions, will render the resolution of image segmentation. The regions that are separated from the other regions vary in different properties such as colour, intensity or texture. The segmented regions of the brain and its contour with WM, GM, and CSF are as shown in the Fig. 2.

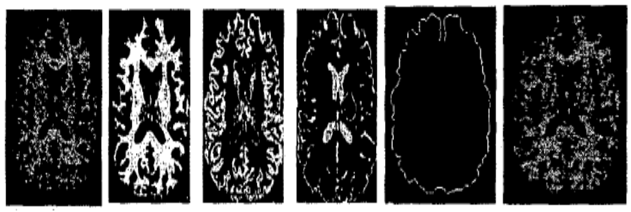


Fig. 2 (a) Brain (b) White matter (c) Grey matter (d) CSF (e) Contour of brain (f) Brain + contour. PC. Shijuan He et.al [1]

The segmentation techniques discussed in this paper with respect to MRI brain images are: Neural Network Model (Self-Organizing Maps (SOM), Radial Basis Function (RBF), Back Propagation (BP)), Fuzzy C-Means (FCM), Deformable Models, Level Set Models, Genetic Algorithm, Differential Evolutionary Algorithm, Hybrid Clustering and Artificial Intelligence.

B. *Neural Network Model*

The Neural network model is mainly composed of segmenting the regions inside the brain MRI image: White Matter (WM), Grey Matter (GM) and Cerebro-spinal fluid (CSF). The neural disorders such as epilepsy, Alzheimer's disease can be detected at the stage of early by the proposed method of Shanthi et.al [17]. The author has designed a system such that it segments the region of the brain using local threshold methods and training using the neural network model. Hussain et.al [18] proposed a system that provides a result based on segmenting the normal tissues from the MRI images such as WM, GM, CSF and also it extracts the tumor from abnormal images to identify the pathological tissues like Edema.

1) *Convolutional Neural Networks*: Convolutional Neural Network is composed of neurons which consist of learnable weights and biases. Ouseph C et al.[9] proposed a reliable tumor detection method based on CNN that reduces the operators and the errors. CNN is used in convolving a signal or an image with kernels to obtain feature maps. The system is divided into two phases: firstly learning/training phase and secondly recognition/testing phase.

The detection of tumor takes place in main three main stages: (1) pre- processing (2) classification by CNN and (3) post-processing .The aim of the project was to detect and extract the of tissue abnormalities by using the biochemical features. The specificity and the sensitivity of the method are evaluated and accuracy is determined.

In the recent papers using CNN, three have utilised an architecture that leverages on the unique attributes of medical data: two use 3D convolutions (Payan and Montana [19]; Hosseini-Asl et al. [20]) instead of 2D to classify patients as having Alzheimer; Kawahara et al. [21] has applied a CNN- like architecture to a brain connectivity graph that was derived from MRI diffusion-tensor imaging

(DTI). For this, they had developed many layers, which formed the basis of their network, so-called edge-to-edge, edge- to-node, and node-to-graph layers. It was used to predict brain development and it outperformed existing methods in assessing cognitive and motor scores.

2) Recurrent Neural Networks: RNNs have become quite relevant in segmentation [22]. Andermatt et al. [23] made use of a complete 3D RNN which had gated recurrent units used to segment grey and white matter in a given brain MRI dataset.

One of the earliest papers on medical image segmentation using deep learning algorithms used patch-trained neural networks and it was published by Ciresan et al. [24]. A number of recent papers use fCNNs (fully convolutional neural networks) which reduce redundant computation.

In this paper, the preprocessing has been done in the MRI of a brain image and the skull has been stripped separately to identify the regions of WM, GM, and CSF. The segmentation of this region has been done in 65 seconds, the training of 56 images using neural networks is done in 595 seconds and the simulation of it with the training set of 120 images has been processed within 97 seconds.

The advantages in Neural networks are that they can easily learn rich representations and are very flexible.

C. Self-Organizing Maps (SOM)

Emambaksh et.al [25] has proposed a method of automatic image segmentation of a brain image using the technique of SOM. In this paper, feature extraction has been used, then dimensionality reduction, followed by SOM which is further helpful in the detection of edges of the image. At last, the watershed segmentation is helpful in segmenting the regions which are considered as a topographical method of region-growing. The advantage of this proposed system is the fast computational speed, which has more free parameters than the other algorithms like FCM and GMM (Gaussian Mixture Model).

The tumor detection and the automated brain image segmentation have been given by K.B.Vaishnavee and K.Amshakala [7] using the SOM-clustering technique. In this paper, the Proximal Support Vector Machine (PSVM) classifier approach has been implemented to get a good result for the high-resolution images under noisy intensity conditions. This concludes that the PSVM classifier can reduce the rate of error and gives a higher accuracy.

Ortiz et.al [4] has proposed a system of hierarchical SOM and probability clustering method in identifying and segmenting the different regions of MRI brain image. This approach consists of the methods like Growing Hierarchical Self-Organizing Maps (GHSOM) and the probability clustering method. This paper implements a segmentation result which gives average metric values of 0.32 for white matter, 0.75 for grey matter and 0.69 for cerebrospinal fluid.

The advantage of SOM is that they are capable of organizing large and complex datasets. The data mapping is also easily interpreted here.

D. Radial Basis Function (RBF)

The brain image segmentation done with the help of RBF neural network proposed by Rostami et.al [26], it decreases with the standard FCM limitations. The mixture of both RBF with the FCM algorithm is combined together to get the segmented regions of the brain image here. This paper concludes that the RBF is used to increase the accuracy in their segmentation results which are corrupted (noise).

Valdes-Cristerna et.al [27] used a combination of RBF network and a spline Active Contour Model (ACM) for segmenting the multispectral MRI of a Brain Image. In this paper, a hybrid model for the multispectral segmentation of an MRI brain image is presented which gives a high quality of performance when measured in terms of Tanimoto indexes.

J.K.Sing et.al [28] proposed a system of self-adaptive radial basis function neural network to segment the regions of the brain. The proposed system in this paper was found more accurate when compared with other methods for modelling the hidden layer of neurons using the conventional k-means algorithm.

RBF neural network has the benefits of easy design, effective tolerance to the input noise, learning ability through online and good generalization.

E. Back Propagation (BP)

Artificial Neural Networks (ANN's) have been presented by Alirezaie et.al [29] with the help of a Back Propagation algorithm to segment the regions of the MRI brain image. They concluded that the supervised multi-spectral MR images have been classified based on the Learning Vector Quantization (LVQ) artificial neural network. This paper implements that the segmentation results can be effective on 250 pixels per class in a 256 x 256 resolution of MR images with a multi-layer back propagation method between 10 to 20 of hidden units and this method also provides relatively fast training and testing. Deepa et.al [6] proposed a system of brain tumor classification and they exploit their capabilities using Back Propagation Network and Radial Basis Function Network. This can be helpful in identifying cancer or noncancer tumor regions with respect to the detection in the tumor region. This paper concludes that the classification accuracy of the Back Propagation Network is about 85.71% and when compared with the RBF network, it gives hopeful results in the classification of brain tumor analysis.

Backpropagation is a very simple and efficient way to compute the gradient in any neural network and has the benefits of versatility and accuracy.

F. Fuzzy C-Means (FCM)

There has been a lot of research done on the FCM method [30], [31], [32], [8], [1], [33], [34], [35]. The brain images of MRI need a computer analysis for the precise delineation of the tumors and then the reproducible method of image segmentation process. This method has been given by Birgani et.al [8] with the clustering algorithm of FCM basis Neural network. This paper concludes a high accuracy and robustness when compared with normal segmentation results at the higher levels of the intensity regions and noise.

Tian Lan et.al [34] had proposed a system for the segmentation of brain image based on kernel FCM technique. The techniques of FCM, Spatial FCM, Kerneled FCM and My FCM are all computed from the brain image and the accuracy factor with the error rate is checked. This paper thus concludes a higher accuracy rate in the method of My FCM than the other methods. Agarwal et.al (2015) [30] had given a system of bias field correction technique integrated with the fuzzy c-means segmentation to partition the brain MRI image into two clusters GM and WM respectively. The level set segmentation is used at last to segment these regions. It is concluded from this paper that the results found were given better accuracy than the other algorithms.

Ping and HongLei Wang [31] proposed a method of modified FCM to segment the regions of an MRI brain image. This proposed method concludes that it can increase the performance in clusters for both the Gaussian and salt-pepper degraded images. Nookala Venu [35] has given a system based on de-noising the MRI of a brain image and segmenting the regions in it.

FCM gives an accurate result for the dataset which is overlapped. The membership to every cluster center is assigned to a data point, which results in a data point representing more than a cluster center.

G. Deformable Models

Huang et.al [36] has proposed a system of a hybrid geometrical deformable model for the automatic segmentation of brain tissues of 3D Brain MRI Image. In this paper, the brain tissue segmentation has been done on both the single & multiple sequences of MRI scans. It is based on the deformable models which give an accurate and stable segmentation. This paper thus concludes that the proposed method has an accuracy with a mean improvement percentage of 8.55 and 10.18 while segmenting the White Matter and Grey Matter tissues. A quick MRI segmentation method in the brain has been obtained by Neeraja Menon and Rohit Ramakrishnan [37] with an integration of the Artificial Bee Colony (ABC) algorithm (evolutionary computing technique) and Fuzzy C-Means (FCM) algorithm, using which the tumor regions of the brain are enhanced in the segmented image.

M.Karnan and T.Logheshwari [38] proposed a system using the Ant Colony Optimization (ACO) hybrid technique with the fuzzy segmentation which extracts the suspicious region of the brain image. This paper gives the position of the tumor region and the pixel similarities. Segmentation of a brain MRI did by Zohra et.al [39] using an ACM through the Greedy algorithm is adopted here. This paper thus concludes that the system will process the energy parameters that are functioning to the specific values which give a good result in the detection rate. The Greedy algorithm in this paper is used here for the benefit of its efficiency, simplicity and less computational time.

The deformable models have the capability to generate directly, the parametric curves that are closed and the image surfaces, to incorporate a smooth constraint throughout the model.

H. Level Set Models

Segmentation of the ventricles and the phantom from the MNI brain web datasets has been done by Ciofolo et.al [40]. The author proposed a fully automated succession of processing for the segmentation of a 3D MRI brain image. This paper gives the improved visualization quality of the thin and low contrast regions of the MRI image, Also, computation time decreased.

Anami et.al [41] had proposed a system of the level set based methodology & modified FCM for automatic brain segmentation into GM, WM, and CSF. This paper concludes that most of the predicted results are considered to be adequate when segmented with modified FCM. The automatic brain segmentation for a tumor in an MRI image has been proposed by Dawngliana et.al [5]. This paper has given a system of hybridized multilevel thresholding to level set, where initially the segmentation will be from multilevel thresholding. Then, a fine portrait region is extracted from the level set method adding to the morphological operations. The hybridized paradigm is more effective when compared to the existing method. Duth et.al [42] proposed a system of RSKFCM and level set method for the segmentation of brain MRI image that gives promising results with a reduced time complexity.

Level set methods have the advantages of versatility, robust and accurate. The resulting techniques are able to hold the sharp type of cusps and corners in the propagating solution, as well as topological changes, and three-dimensional effects.

I. Evolutionary Algorithm

Ghassabeh et.al [43] proposed a method of improver FCM algorithm that has been used to segment the brain MRI image using the optimization method in the genetic algorithm. This paper concludes that the noisy images have been segmented using the efficient segmentation method that results in a good rate to get the desired values. Jansi & Subashini [44] proposed a method of clustering the brain image with the help of clustering methods such as K-Means and FCM using the Genetic algorithm. The fuzzy c-means method is more effective in the segmentation of the fuzzy boundary region, but there is no more beneficial path to find the global centroid value. In this paper, to overcome this type of issue, the Genetic algorithm is integrated with FCM to determine the global centroid value.

Balafar et.al [45] had proposed a system of segmenting the brain image using a combination of genetic algorithm and FCM. This proposed system is used in initializing the center of the clusters identified genetic algorithm, then achieved by the minimization of the function. Sriparna Saha and Sanghamitra Bandyopadhyay [38] presented a method of fuzzy-VGAPS which automatically segments the brain tissue classes and also provides better results than the other two methods.

Kumar et.al [46] has proposed a system of segmenting the MRI of a brain image using the evolutionary computational technique. This paper thus concludes that the Robust Spatial Kernelled FCM (RSKFCM) with genetic algorithm provides better results than the other FCM methods.

Evolutionary algorithm optimizers have an advantage of scaling to high dimensional problems. Moreover, the algorithm may be easily adjusted, changed and can be customized.

J. Hybrid Clustering

Pitiot et.al (2002) [47] proposed an automated technique for extracting the anatomical structure from the sequence of

MRI brain images using the texture information. This consists of a two stage hybridized neural classifier which involves the stages of texture classification and local shape/texture analysis. This paper concludes that it achieves both better classification results and a faster convergence. The automatic segmentation of the brain tumor is further identified by Dawngliana et.al [5] using the hybridized method of multi-level thresholding and level set. This paper concludes that the proposed method provides an impressive performance where the thresholding method is used to segment the tumor region in multiple levels and the level set method is used without the re-initialization technique to extract the fine portrait of a tumor area.

Dynamic fuzzy Clustering using Harmony Search (DCHS) algorithm has been given by Moh'd Alia et.al [48] is used for the automatic detection of the appropriate number of clusters and also it identifies the location of cluster centers. This paper concludes that the hybrid harmony search algorithm has been very useful in segmenting the brain images into the number of clusters as required. T.Logeswari and M.Karnan [49] used the method of Hybrid Self Organizing Map (HSOM) which has been implemented to provide the MRI brain segmentation in the 3x3, 5x5, 7x7, 9x9 and 11x11 windows of the neighbouring pixels. The region of the interest will be far better for the observer who perceives the region.

The hybrid clustering enables good computational and conceptual simplicity. The greater part of the clustering algorithms shows better results for numerical data that have ordered values. The combination of the tree structures and clustering reduces diminishes the disadvantages of the previous structure.

K. *Artificial Intelligence*

Megersa et.al [50] has proposed a system of tumor segmentation using hybrid intelligent fuzzy Hopfield neural network. In this paper, the fast c-means based fuzzy Hopfield neural network algorithm is used to extract the region of a brain tumor and detect it visually. Thus the paper concludes that the proposed framework has the advantages of segmenting the regions of normal tissues in brain MRI images and also both the enhanced & non-enhanced tumors by fusing the weighted images.

M.Y.Bhanumurthy and Koteswararao Anne [51] proposed an ABC algorithm that gives an efficient type of fitness function, which improves the segmentation quality. Automated detection has been accomplished by this proposed technique. This paper implements the segmentation of the tumor and automated detection, which contains three stages: i) feature extraction, ii) classification and iii) segmentation, where the classification is based on Neuro-fuzzy based system and the technique of region-growing is implemented for segmenting the tissues of the tumor.

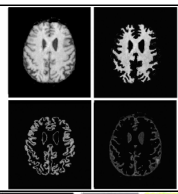
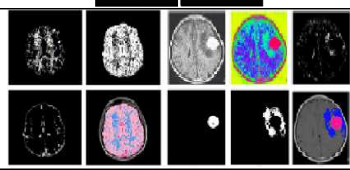
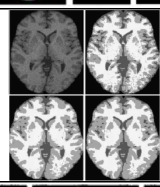
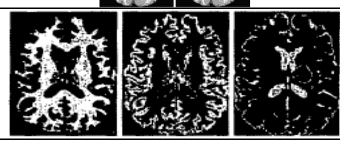
The error is minimized in Artificial Intelligence and. With greater precision, accuracy is achieved. It also carries out repetitive and time-consuming jobs efficiently.

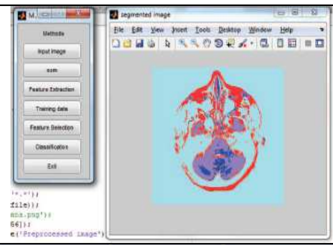
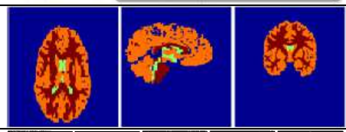
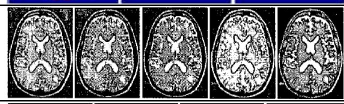
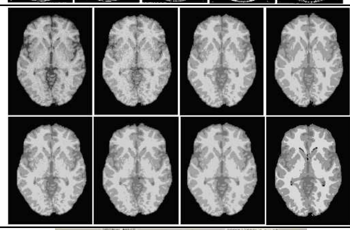
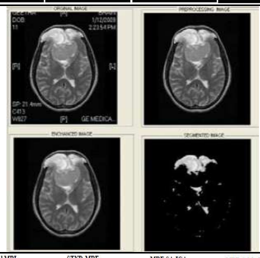
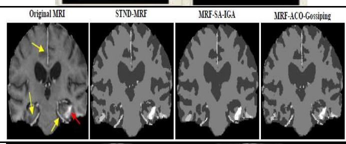
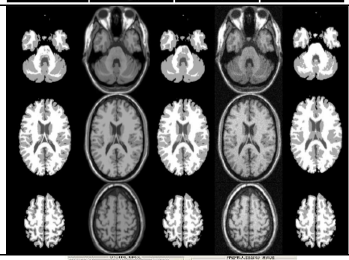
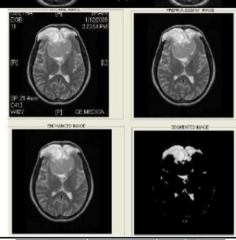
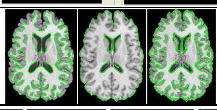
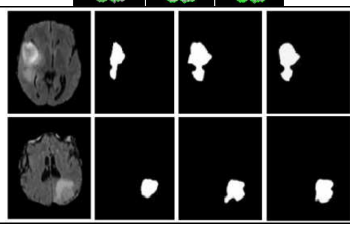
III. Results and Discussion

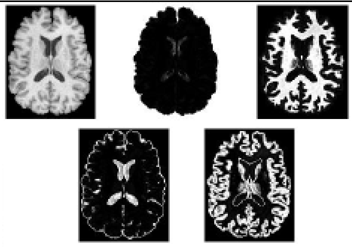
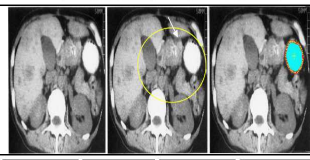
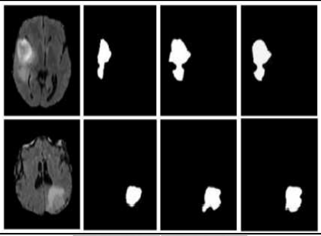
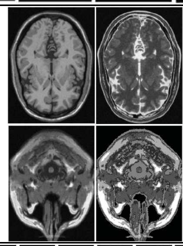
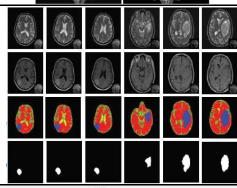
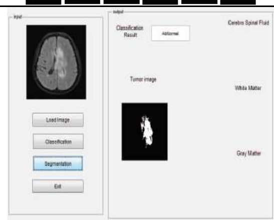
A. *Summary of the Segmentation Methods*

The summaries of all the literature survey using the segmentation methods have been tabulated as Table 1 is shown below,

TABLE I
Summary of the Segmentation Methods

Segmentation Methods	**Author's Name**	**Segmented Region**	**Methodology Used**	
Neural Networks	Shanthi et.al [17]	WM, GM, and CSF	Hybrid method of thresholding and neural network model	
	Hussain et.al [18]	WM, GM and CSF, and Tumor, Edema	Feed-Forward Back Neural Network (FFBNN), Region Growing and thresholding.	
Fuzzy C-Means (FCM)	Birgani and Asadi [8]	WM, GM, and CSF	FCM clustering algorithm	
	Shijuan-He et.al [1]	WM, GM, CSF and contour of the brain	Histogram based Fuzzy C-Means algorithm, multi-scale connectivity-restrained clustering algorithm	

Self-Organizing Maps (SOM)	Vaishnavee and Amshakala [7]	Tumor	HFS-SOM and Proximal Support Vector Machine (PSVM) classification method	
	Ortiz et.al [4]	WM, GM, and CSF	Growing Hierarchical Self-Organizing Maps	
Radial Basis Function (RBF)	Sing et.al [28]	WM, GM and CSF	Self-adaptive Radial Basis Function (RBF)	
	Rostami et.al [26]	WM, GM and CSF	FCM, RBF Neural Network	
Back Propagation	Karnan and Gopal [29]	WM, GM, and CSF	Markov Random Field, Hybrid Parallel Ant Colony Optimization	
	Yousefi and Azmi [6]	Tumor	Markov Random Field (MRF); Simulated Annealing (SA)	
Deformable Models	Huang et.al [36]	WM, GM, and CSF	Deformable models, Edge-Based Geodesic Active Contour	
	Karnan and Logheshwari [38]	Tumor	Ant Colony Optimization with fuzzy segmentation	
Level Set Models	Anami and Unki [41]	WM, GM, and CSF	Level Set Model with fuzzy segmentation	
	Deb et.al [5]	Tumor	Multilevel thresholding, Level set method	

Evolutionary Computing	Kumar et.al [46]	Normal brain images into 4 clusters	Robust Spatial Kernel FCM (RSKFCM), Genetic algorithm based FCM	
	Zohra et.al [39]	Lesion Detection	Greedy algorithm, Evolutionary algorithm	
Hybrid Clustering	Deb et.al [5]	Tumor	Multilevel thresholding, level set method	
	Alia and Aziz [48]	Multiple sclerosis lesions into 6 clusters, Normal brain image into 9 clusters	Dynamic Clustering Harmony Search (DCHS)	
Artificial Intelligence	Megersa and Alemu [50]	Tumor	Fuzzy Hopfield Neural Network, Intelligence algorithms	
	Bhanumurthy and Anne [51]	Tumor	Neuro-fuzzy classifier, Region growing method	

B. Observations from the Literature Survey

The following observations were made,

1) From the study of these papers, it has been observed that the technique of Fuzzy C-Means is commonly used for all research. The traditional type of Fuzzy C-Means works well for segmentation in the exemption of noise.

2) The segmentation of the three regions from the MRI of a brain image, namely WM, GM, and CSF has been done in most of the research papers that can be helpful in identifying the neural disorders such as epilepsy, Alzheimer's disease at the early stage.

3) It is observed that there is no singular algorithm that is used to segment all the regions from the MRI of a brain image. Multiple algorithms should be used to satisfy the segmentation results.

4) From the above study, it is evident that there is a lot of work in progress on 3D MRI brain image segmentation and tumor detection.

5) The survey above shows that the hybrid segmentation technique can be used for partitioning the MRI of a brain image into more than 3 regions.

6) Radial Basis Function neural network has advantages of tolerance to the input noise, i.e. the Gaussian and Salt Peppered noise from the MRI of a brain image will give good results.

IV. CONCLUSION

In this paper, the advanced segmentation methods used for partitioning the regions of MRI brain image have been discussed in detail. There is a lot of scope for further research due to the challenges present in the characteristics of the brain image. It has been observed from the survey that each segmentation method has its own merits and demerits. There is no singular algorithm that satisfies the partitioning of all regions in the MRI brain images. Hence, there is a need to find the best possible technique or hybrid techniques that can aid in the automatic segmentation of all parts. In this regard, we feel that this survey would be useful for researchers.

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